IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received November 23, 2021, accepted December 18, 2021, date of publication December 28, 2021, date of current version January 12, 2022.

Digital Object Identifier 10.1109/ACCESS.2021.3139084

The New Model of Game Cross Efficiency DEA With Index Groups and an Application to Land Utilization Efficiency

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This work was supported in part by the National Social Science Foundation of China under Grant 19BGL214, in part by the National Natural Science Foundation of China Grant 71563015 and Grant 11661030, and in part by Jiangxi Postgraduate Innovation Special Fund Project under Grant 23.

ABSTRACT In recent decades, the data envelopment analysis (DEA) model has been applied to various fields. However, the current research on DEA for land utilization efficiency is based on the assumption that each decision making unit (DMU) is independent and does not distinguish different preference to output indexes. Therefore, this paper proposes a new game cross efficiency model which considers the different levels of concern to different output indexes. In the proposed model, the output indexes are divided into several groups and DMUs present their preferences to these groups. Subsequently, this paper develops an algorithm to solve this model and proves the convergence of the algorithm. Then, taking the evaluation of land utilization efficiency as an example, the importance of game cross efficiency and group indexes in evaluations is presented. The output indexes are separated as two classes including economy output indexes and environment output indexes. The land utilization efficiency of cities in Pearl River Delta in 2019 is evaluated by the proposed model. The analysis shows that when there is a significant difference between different groups of output indexes, the ranking result for decision making units is different from the traditional DEA. The model reveals that the efficiency of some cities depends much on some special output indexes.

INDEX TERMS Data envelopment analysis, linear programming, game theory, cross efficiency, land evaluation.

I. INTRODUCTION

Land resources are not only the material carrier of urban economy, but also non renewable resources. Therefore, the efficiency of land utilization directly affects the social and economic development. With the increasing rate of Chinese urbanization year by year, the scale of urban land continues to expand and the land problems are becoming more and more serious, such as extensive land use, unreasonable urban land use structure, land storage without use, etc. The research on the evaluation of urban land use efficiency is of great significance for the efficiency and sustainable use of land.

High efficient utilization of resources can reflect high management level of enterprises and governments to some extent. Since the resources, such as the land resources, and time are limited, it is crucial for enterprises and government departments to make full use of these resources. Evaluating the management level of enterprises and governments through some appropriate methods is necessary, which can assist managements to improve work. Furthermore, the evaluating result can provide the direct information for leaders to identify the valuable enterprises and departments and avoid whipping the fast and hard-working, i.e., unfair punishment.

Various factors should be considered to comprehensively and objectively evaluate the enterprises or government departments. These factors include the input indexes and output indexes. Input indexes are something that required in the process of production and management, such as capital and labor. Output indexes refer to the quantity of products produced, the economic or social benefits and so on.

In 1978, Charnes, Cooper and Rhodes proposed data envelopment analysis (DEA) methods [1] to evaluate the relative effectiveness of enterprises or government departments with multiple input indexes and output indexes. The relative

The associate editor coordinating the review of this manuscript and approving it for publication was Muhammad Ali Babar.

effectiveness can represent the management level mentioned of the enterprise or government beforehand that relative to others.

Generally, the DEA model proposed by Charnes, Cooper and Rhodes in 1978 is also called CCR model. DEA calculates the maximum efficiency of a decision making unit (DMU) by constructing a mathematic programming model which aims at maximizing the ratio of output to input. Generally, if ratio of output to input is equal to 1, then the DMU is DEA efficient. In the process of solving the ratio, DEA fulfills a non-parameter estimation [2]–[4].

In recent years, scholars at home and abroad have carried out a lot of research on the Chinese land utilization efficiency. Foreign studies focus on the relationship between land intensive utilization and efficiency evaluation, economic development and land utilization efficiency. Based on these studies, domestic researchers study a large number of empirical analyses, such as efficiency measurement and evaluation, regional differences, influencing factors, policy optimization and so on.

Since the evaluation of land utilization efficiency involves a lot of input indexes and output indexes and the DEA model is a quite useful method to evaluate the relative effectiveness of similar departments with multiple inputs, especially multiple outputs, many scholars study the land utilization efficiency based on the DEA model in recent decades. Zhang *et al.* [5] pointed out that there is an increasing trend of the utilization efficiency for urban construction land of the provincial capitals. Zhang *et al.* [6] discovered that the utilization efficiency of a piece of land has a close relation with its distance to the center of the city. Zhu *et al.* [7] found out that there are some significant differences of efficiency for different districts in a city.

Although fruitful achievements are obtained, some challenges still need to be addressed.

(1) It can be found that the current DEA studies on land utilization efficiency only focus on the DMU itself evaluation and the impacts between DMUs are not fully considered. In fact, there is a fierce competition for the performance between local governments. The governments are DMUs in these studies. A local government will consider the reaction of other local governments on its land supply, especially when the local governments are being neighborhoods. Therefore, regardless of the mutual evaluation and game competition between DMU, these studies on the land utilization efficiency may lead to inaccurate efficiency evaluation.

(2) In addition, the current DEA studies on land utilization efficiency are based on the assumption that each DMU has the same preference on all output indexes. In practice, it is relatively easy for DMUs to determine a preference between some groups of indexes. Then, how to design the evaluation model to reflect the preference and the unknown priorities is an interesting and import issue. For example, assume there are two groups of output indexes and each group has two indexes: (a) an industry increment index, a regional GNP; (b) a habitat conservation index, an environmental index. A DMU prefers the group (b) on the whole, but has no exact priorities between the indexes in the group (b) and cannot definitely determine that whether each index in the group (b) is important than each index in the group (a). How to model this situation?

(3) The difficulty on land utilization evaluation is how to determine the priorities of output indexes for DMUs. However, it is nearly impossible to give an exact priority for each output index, such as land sale revenues, industry increment indexes, regional gross national product (GNP) and environmental indexes.

As mentioned above, this paper firstly divides the indexes into several groups. Subsequently, DMUs provide preference on these groups, which avoids giving an exact priority for each index. Hence, this paper designs a new game cross efficiency DEA model. Then, this paper develops an algorithm to solve this model and proves the convergence of the algorithm. Finally, the model is applied to the evaluation of land utilization efficiency of 9 cites in Pearl River Delta in China. The result shows that the model has a better discernibility than CCR model. Furthermore, by adjusting parameters in the model, this paper concludes that some cities have more dependency on some indexes than other cities.

The remainder of this paper unfolds as follows. Section II briefly reviews the literature related to the DEA model and its application. Section III introduces the preliminaries concerning the CCR model, the DEA efficiency and average game cross efficiency of DMU. Then, the improved game cross efficiency model and the solving algorithm are proposed in Section IV. Convergence of the solving algorithm is also proved in this section. Section V applies the proposed model to evaluating the land utilization efficiency of the Pearl River Delta City (PRD) Cluster. Finally, this paper ends with some concluding remarks and future research discussions in Section VI.

II. LITERATURE REVIEW

This section briefly reviews the existing research on the DEA model and its applications.

In the classical DEA model, each DMU is independent and does not affect each other. However, in real life, enterprises and departments are dependent and often connect with each other. Thus, considering the competition among DMUs, Banker [8] combined DEA and game theory and revealed the relation between DEA and two persons zero-sum game without constraints. In addition, some scholars [9]–[12] further dug the closely relations between DEA and game with constraints. Considering the mutual evaluation between DMUs, Sexton *et al.* [13] proposed the concept of cross efficiency which is widely applied to various fields [14]–[16]. Since the non-uniqueness of the optimal solutions may improve the cross efficiency of some DMUs but at the expense of others, Liang *et al.* [16] generalized the original DEA cross-efficiency concept to game cross efficiency by integrating cross efficiency and game theory. Furthermore, Liang *et al.* [16] proved that there is an equivalence between the value of the game cross efficiency and some Nash equilibria for the game with a special continuous concave payoff. Based on the game cross efficiency, many scholars made fruit achievements with further in-depth study [17]–[20]. For instance, Li and Xu [19] gave a new game model with the cross efficiency by considering some constraints on DMUs that are not DEA efficient. Zhang and Gong [20] introducing the priority to multi-objectives into game cross efficiency models.

Since the effectiveness and superiority of these methods, DEA models are applied to various fields, such as the root cause identification for vibration and noise failure of washing machine [21], the evaluation on the performance of pallet rental companies [22], [23], the performance evaluation on system of logistics enterprises [24], the selection of the most suitable locations to host wind power plants [25] and so on.

III. PRELIMINARIES

The DEA proposed by Charnes, Cooper and Rhodes (1978), i.e., CCR model, is briefly introduced as follows. Let $x_{ij}(i = 1, 2, \ldots, s)$ be the i-th input of the DMU $j(j = 1, 2, \ldots, n)$ and $y_{rj}(r = 1, 2, \ldots, m)$ be r-th output of the DMU j. DEA evaluates the efficiency of DMU by the ratio of output to input. The efficiency of DMU j $(j = 1, 2, \ldots, n)$ is obtained by solving the mathematical programming given below.

$$max \ \frac{\sum_{r=1}^{m} \mu_{rj} y_{rj}}{\sum_{i=1}^{s} w_{ij} x_{ij}}$$
$$s.t. \begin{cases} \dfrac{\sum_{r=1}^{m} \mu_{rj} y_{rl}}{\sum_{i=1}^{s} w_{ij} x_{il}} \leq 1, & l = 1, 2, \ldots, n; \\ w_{ij} \geq 0, & i = 1, 2, \ldots s; \\ \mu_{rj} \geq 0, & r = 1, 2, \ldots m \end{cases} \tag{1}$$

where μ_{rj} and w_{ij} are the weights of r-th output and i-th input of DMU j, respectively. Generally, if ratio of output to input is equal 1, then the DMU is DEA efficient. To overcome the unboundedness of the objective in Eq. (1), the above model can be rewritten as:

$$max \ \sum_{r=1}^{m} \mu_{rj} y_{rj}$$
$$s.t. \begin{cases} \sum_{i=1}^{s} w_{ij} x_{il} - \sum_{r=1}^{m} \mu_{rj} y_{rl} \geq 0, & l = 1, 2, \ldots, n; \\ \sum_{i=1}^{s} w_{ij} x_{ij} = 1 & \\ w_{ij} \geq 0, & i = 1, 2, \ldots s; \\ \mu_{rj} \geq 0, & r = 1, 2, \ldots m; \end{cases} \tag{2}$$

In the classical DEA model, each DMU constructs the programming and determines the optimal weights of inputs and outputs to maximize its efficiency, which may cause the biases in efficiency ranking of DMUs by comparing these obtained efficiencies. Therefore, the concept of cross efficiency are proposed by Sexton et al. [13]. The average cross efficiency value of DMU j can be calculated as follows:

Firstly, take an arbitrary DMU $d(d = 1, 2, \ldots, n)$, the optimal weights of inputs and outputs can be derived by solving Eq. (2). Denote the optimal weights of r-th output and i-th input of DMU d by μ^*_{rd} and w^*_{id}, respectively.

Then, the cross efficiency of DMU j relative to DMU d are calculated as follows:

$$E_{dj} = \frac{\sum_{r=1}^{m} \mu^*_{rd} y_{rj}}{\sum_{i=1}^{s} w^*_{id} x_{ij}}, \quad (d, j = 1, 2, \ldots n) \tag{3}$$

Finally, the average cross efficiency value of DMU j, can be derived as follows:

$$\overline{E}_j = \frac{1}{n} \sum_{d=1}^{n} E_{dj}, \quad (j = 1, 2, \ldots n) \tag{4}$$

According to the average cross efficiency values $\overline{E}_j(j = 1, 2, \ldots n)$, the efficiency ranking of DMU is obtained. Since the optimal solution of Eq. (2) is not unique, the cross efficiency in Eq.(3) and the efficiency ranking obtained by the average cross efficiency value in Eq. (4) is not unique.

Considering the competition between DMUs, and the non-uniqueness of cross efficiency, each DMU aims to maximize its efficiency by optimizing its input combination. Liang et al. [16] introduced the game cross efficiency β_{dj} as follows to denote the cross efficiency of DMU j relative to DMU d.

$$\beta_{dj} = \frac{\sum_{r=1}^{m} \mu_{rj}(\alpha^*_d) y_{rj}}{\sum_{i=1}^{s} w_{ij}(\alpha^*_d) x_{ij}} \tag{5}$$

where $\mu_r(\alpha^*_d)$ and $w_i(\alpha^*_d)$ are the feasible solution of Eq. (6) and the optimum solutions of the following Eq. (6).

$$max \ \theta_j(\alpha_d) = \sum_{r=1}^{m} \mu_{rj} y_{rj}$$
$$s.t. \begin{cases} \sum_{i=1}^{s} w_{ij} x_{il} - \sum_{r=1}^{m} \mu_{rj} y_{rl} \geq 0, \\ \quad l = 1, 2, \ldots, n; \\ \sum_{i=1}^{s} w_{ij} x_{ij} = 1 \\ \alpha_d \sum_{i=1}^{s} w_{ij} x_{id} - \sum_{r=1}^{m} \mu_{rj} y_{rd} \leq 0 \\ w_{ij} \geq 0, \\ \quad i = 1, 2, \ldots s; \\ \mu_{rj} \geq 0, \\ \quad r = 1, 2, \ldots m \end{cases} \tag{6}$$

where α_d is a parameter and $\alpha_d \leq 1$. The algorithm for Eq. (6) is briefly described as follows. A DMU j maximizes its efficiency under the condition that its given efficiency α_d for the DMU d is not decreased. There exists a corresponding game which arrives at its equilibrium when all DMUs reaches its optimal efficiency α^*_j. For the computation of the value of game cross efficiencies, the algorithm in Liang et al. [16] is introduced as follows:

Let $\alpha^0_d = \overline{E}_d(t = 0)$ be the initial value of α_d, where t represents the number of iterations. $\mu^*_r(\alpha^t_d)$ and $w^*_i(\alpha^t_d)$ are optimum solutions of Eq. (6), and the corresponding optimum value is $\theta_j^*(\alpha_d^t)$. When it reaches the $(t+1)$-th iteration, let $\alpha_j^{t+1} = \frac{1}{n}\sum_{d=1}^{n}\theta_j^*(\alpha_d^t)$. After α_d^t tends to α_d^*, define an average game cross efficiency (**CCG**) as:

$$\beta_j = \frac{1}{n}\sum_{d=1}^{n}\theta_j^*(\alpha_d^*) = \frac{1}{n}\sum_{d=1}^{n}\beta_{dj}, \quad (j=1,2,\ldots n) \tag{7}$$

Thus, the average CCG β_j, is unique and it can be utilized to rank the efficiency ranking of DMUs. Since the initial value of the parameter α_d^0 is $\overline{E}_d$, Eqs. (3) and (4) are also used in this algorithm.

IV. THE IMPROVED GAME CROSS EFFICIENCY MODEL

In this section, this paper divides all output indexes into two groups. For convenience, rearrange the order of all output index and denote the first group of output indexes by $1,2,\ldots,k$ and the second group of output indexes by $k+1, k+2,\ldots,m$. All DMUs prefer the second group of indexes than the first group of indexes. On the basis of Eq. (2) and (6), this paper establishes the models in Eqs. (8) and (9):

$$\max\ \theta_j = \sum_{r=1}^{m}\mu_{rj}y_{rj}$$
$$s.t.\begin{cases}\sum_{i=1}^{s}w_{ij}x_{il} - \sum_{r=1}^{m}\mu_{rj}y_{rl} \geq 0, & l=1,2,\ldots,n;\\ \sum_{i=1}^{s}w_{ij}x_{ij} = 1 & \\ \sum_{r=1}^{k}\mu_{rj} \leq \sum_{r=k+1}^{m}\mu_{rj} & \\ w_{ij}\geq 0, & i=1,2,\ldots s;\\ \mu_{rj}\geq 0, & r=1,2,\ldots m\end{cases} \tag{8}$$

where the constraint $\sum_{r=1}^{k}\mu_{rj} \leq \sum_{r=k+1}^{m}\mu_{rj}$ represents that the sum weight of the second group of output indexes is higher than that of the first group of output indexes. In other word, DMU j prefer the second group of output indexes. However, it should be pointed out that the weights of some output indexes in the first group may still higher than that in the second group since the constraint $\sum_{r=1}^{k}\mu_{rj} \leq \sum_{r=k+1}^{m}\mu_{rj}$ only represents the relationship between the sum weights. Denote the optimal value of Eq. (8) by $\boldsymbol{\theta_j^*}$ (call it **ICCR**) for each DMU $j(j=1,2,\ldots,n)$. Then, based on Eq. (8), the following programming is presented in Eq., (9)

$$\max\ \theta_j(\overline{\alpha}_d) = \sum_{r=1}^{m}\mu_{rj}y_{rj}$$
$$s.t.\begin{cases}\sum_{i=1}^{s}w_{ij}x_{il} - \sum_{r=1}^{m}\mu_{rj}y_{rl} \geq 0,\\ \qquad l=1,2,\ldots,n;\\ \sum_{i=1}^{s}w_{ij}x_{ij} = 1\\ \overline{\alpha}_d\sum_{i=1}^{s}w_{ij}x_{id} - \sum_{r=1}^{m}\mu_{rj}y_{rd} \leq 0\\ \sum_{r=1}^{k}\mu_{rj} \leq \sum_{r=k+1}^{m}\mu_{rj}\\ w_{ij}\geq 0,\\ \qquad i=1,2,\ldots s;\\ \mu_{rj}\geq 0,\\ \qquad r=1,2,\ldots m\end{cases} \tag{9}$$

Denote the optimal value of Eq. (9) by $\theta_j^*\left(\overline{\alpha}_d^t\right)$, $(j=1,2,\ldots n)$ when $\overline{\alpha}_d = \overline{\alpha}_d^t, d\in\{1,2,\ldots,n\}$. Then, the average game cross efficiency value of DMU j in $(t+1)$-th iteration is obtained as follows:

$$\overline{\alpha}_j^{t+1} = \frac{1}{n}\sum_{d=1}^{n}\theta_j^*\left(\overline{\alpha}_d^t\right), \quad (j=1,2,\ldots n), \tag{10}$$

Algorithm (IA): According to the iteration relation of Eq. (10), the algorithm for the limit of $\overline{\alpha}_d^t$ is given as below:

(*i*) Let $t=1, \overline{\alpha}_d = \overline{\alpha}_d^t$ and $\overline{\alpha}_d^t = \theta_d^*, d=1,2,\ldots,n$;

(*ii*) Solve Eq. (9). According to Eq. (10), the new average game cross efficiency value $\overline{\alpha}_d^{t+1}$ is obtained.

(*iii*) If for each DMU $j(j=1,2,\ldots n)$, it holds that $\left|\overline{\alpha}_j^{t+1} - \overline{\alpha}_j^t\right| < \varepsilon$, then the algorithm terminates. Otherwise, let $\overline{\alpha}_d = \overline{\alpha}_d^{t+1}$ in Eq. (9) and go to (*ii*).

As $\overline{\alpha}_d^t$ tends to $\overline{\alpha}_d^*$, $d=1,2,\ldots n$, the game cross efficiency (**ICCG**) of DMU j can be calculated as follows

$$\overline{\beta}_j = \frac{1}{n}\sum_{d=1}^{n}\theta_j^*(\overline{\alpha}_d^*), \quad (j=1,2,\ldots n), \tag{11}$$

It should be noticed that the algorithm mentioned above does not use Eqs. (3) and (4).

The following Theorem 1 proves the convergence of (IA).

Theorem 1: The algorithm (IA) is convergent.

Proof: Denote the feasible region of Eq. (9) by $\Delta_j\left(\overline{\alpha}_d^t\right)(j=1,2,\ldots n)$ in t-th iteration. Take an arbitrary DMU $j(j=1,2,\ldots n)$, if $d=j$, then $\theta_j^*\left(\overline{\alpha}_d^1\right) = \theta_j^*$ is hold; if $d\neq j$, then $\theta_j^*\left(\overline{\alpha}_d^1\right) \leq \theta_j^* = \overline{\alpha}_j^1$ due to that the feasible region $\Delta_j(\overline{\alpha}_d^t)$ of Eq. (9) may decrease by comparing with the feasible region of Eq. (8). Therefore, for each DMU $j(j=1,2,\ldots n)$, the following inequality is hold.

$$\overline{\alpha}_j^2 = \frac{1}{n}\sum_{d=1}^{n}\theta_j^*(\overline{\alpha}_d^1) \leq \frac{1}{n}\sum_{d=1}^{n}\theta_j^* = \overline{\alpha}_j^1.$$

For $\overline{\alpha}_d^1$ and $\overline{\alpha}_d^2$, the feasible region of Eq. (9) satisfies: $\Delta_j(\overline{\alpha}_d^1)\subseteq\Delta_j(\overline{\alpha}_d^2)$; then

$$\overline{\alpha}_j^2 = \frac{1}{n}\sum_{d=1}^{n}\theta_j^*(\overline{\alpha}_d^1) \leq \frac{1}{n}\sum_{d=1}^{n}\theta_j^*(\overline{\alpha}_d^2) = \overline{\alpha}_j^3.$$

Noting that θ_j^* is the optimal value of Eq. (8) and for any t, the feasible region of (9), is always small than that of Eq. (8), then one has

$$\overline{\alpha}_j^2 \leq \overline{\alpha}_j^3 \leq \overline{\alpha}_j^1,$$

hence, it holds that

$$\Delta_j(\overline{\alpha}_d^1)\subseteq\Delta_j(\overline{\alpha}_d^3)\subseteq\Delta_j(\overline{\alpha}_d^2).$$

It follows that

$$\overline{\alpha}_j^2 \leq \overline{\alpha}_j^4 \leq \overline{\alpha}_j^3 \leq \overline{\alpha}_j^1.$$

Similarly, one can get

$$\overline{\alpha}_j^2 \leq \overline{\alpha}_j^4 \leq \overline{\alpha}_j^6 \leq \overline{\alpha}_j^5 \leq \overline{\alpha}_j^3 \leq \overline{\alpha}_j^1.$$

Then, one has

$$\begin{aligned}\overline{\alpha}_j^2 &\leq \overline{\alpha}_j^4 \leq \overline{\alpha}_j^6\cdots\\ &\leq \overline{\alpha}_j^{2t} \leq \overline{\alpha}_j^{2t+2} \leq \overline{\alpha}_j^{2t+1} \leq \overline{\alpha}_j^{2t-1}\cdots\\ &\leq \overline{\alpha}_j^5 \leq \overline{\alpha}_j^3 \leq \overline{\alpha}_j^1.\end{aligned}$$

That is,

$$\left|\overline{\alpha}_j^{2t+1} - \overline{\alpha}_j^{2t+2}\right| \leq \left|\overline{\alpha}_j^{2t} - \overline{\alpha}_j^{2t-1}\right|, \quad t = 1, 2, \ldots$$

Therefore, when $t \to \infty$, the average game cross efficiency value $\overline{\alpha}_j^t$ is convergent for each DMU $j(j = 1, 2, \ldots, n)$. Additionally, the number of the output index is finite, thus the algorithm (IA) is convergent for all sequences for a given accuracy ε. This completes the proof of Theorem 1.

Remark 1: Since the initial values of the algorithm (IA) proposed in this paper and the algorithm in [16] are different, the relationship between the average game cross efficiency value of DMU $j\overline{\alpha}_j^t$ in the whole iteration is different from that of [16].

Remark 2: If the output indexes are not divided into different groups there is no $\sum_{r=1}^{k} \mu_r \leq \sum_{r=k+1}^{m} \mu_r$ in Eqs. (8) and (9), then Eqs. (8) and (9) is reduced to Eqs. (2) and (6), respectively. Comparing with the algorithm in Liang *et al.* [16], the proposed algorithm (IA) can solve not only the models in Eqs. (2) and (6) but also in Eqs. (8) and (9). Furthermore, if the model does not take the different group of output index into account, the proposed Algorithm (IA) improves and simplifies the convergence proof to compute the values of CCG by omitting to solve Eqs. (3) and (4). The example for the comparing of the two algorithms is given in the next section.

Additionally, if the output indexes are divided into several groups, then the corresponding models can be established by method similar to Eqs. (8) and (9). For example, if the output indexes is divided to K_1, K_2 and K_3 satisfying $1, 2, \ldots, n = K_1 \cup K_2 \cup K_3$ and $K_p \cap K_h = \emptyset, p \neq h, \forall p, h \in \{1, 2, 3\}$. If and DMU prefers most to the group K_3, and pays more attention to K_2 than K_1, then the model can be constructed in the following Eqs. (12) and (13). The constructed model can be solved by a revised algorithm according to algorithm (IA), too.

$$\max\ \theta_j = \sum_{r=1}^{m} \mu_r y_{rj}$$
$$s.t. \begin{cases} \sum_{i=1}^{s} w_i x_{il} - \sum_{r=1}^{m} \mu_r y_{rl} \geq 0, \\ \qquad l = 1, 2, \ldots, n; \\ \sum_{i=1}^{s} w_i x_{ij} = 1 \\ \sum_{r\in K_1} \mu_r + \sum_{r\in K_2} \mu_r \leq \sum_{r\in K_3} \mu_r \\ \sum_{r\in K_1} \mu_r \leq \sum_{r\in K_2} \mu_r \\ w_i \geq 0, \\ \qquad i = 1, 2, \ldots s; \\ \mu_r \geq 0, \\ \qquad r = 1, 2, \ldots m \end{cases} \tag{12}$$

and

$$max\ \theta_j(\alpha_d) = \sum_{r=1}^{m} \mu_r y_{rj}$$
$$s.t. \begin{cases} \sum_{i=1}^{s} w_i x_{il} - \sum_{r=1}^{m} \mu_r y_{rl} \geq 0, \\ \qquad l = 1, 2, \ldots, n; \\ \sum_{i=1}^{s} w_i x_{ij} = 1 \\ \alpha_d \sum_{i=1}^{s} w_i x_{id} - \sum_{r=1}^{m} \mu_r y_{rd} \leq 0 \\ \sum_{r\in K_1} \mu_r + \sum_{r\in K_2} \mu_r \leq \sum_{r\in K_3} \mu_r \\ \sum_{r\in K_1} \mu_r \leq \sum_{r\in K_2} \mu_r \\ w_i \geq 0, \\ \qquad i = 1, 2, \ldots s; \\ \mu_r \geq 0, \\ \qquad r = 1, 2, \ldots m \end{cases} \tag{13}$$

V. APPLICATION TO PEARL RIVER DELTA CITY CLUSTER

A. THE CHOOSE OF INPUT AND OUTPUT INDEXES

The Pearl River Delta City (PRD) Cluster is the most representative city cluster in China, which has 54800 km^2, 30.5% of the gross area of the Guangdong province. The PRD city cluster includes 9 adjacent cities: Guangzhou, Shenzhen, Dongguan, Zhuhai, Foshan, Zhongshan, Jiangmen, Huizhou and Zhaoqing. Since the year of applying the open policy, the population in PRD has expanded rapidly. To improve the economy and seize the developing opportunity, the construction land of these cities are expanded dramatically; the ecological risk is increasing significantly; the land utilization problems are emerging. In general, there are close dependent and competitive relations between these cities. This phenomenon leads to the fact that there are mutual impact for their decisions on land utilization. This section applies the improved game cross DEA model in **Section IV** to the evaluation of land utilization efficiency in 2019. The evaluation results can be the reference for governments to having an insight into the level of the land utilization efficiency.

In term of the input of the land utilization, this paper takes land resource, capital and labor force into account according to [5]–[7]. The land resource includes the land area for industrial (IL), commercial service land (CL), residential land (RL) and other using (OL). The capital is represented by the investment in fixed assets (IF). The labor force is denoted by the resident population (RP) at the end of the year. These input indexes are listed in Table 1.

The output of the land utilization can be divided into the economic output and environmental output. The revenue from the sale of land (RSL), the regional GDP per capita (GDP) and represent the economic benefit and the value-added of the secondary industry (VSI) and tertiary industry (VTI) belong to the economic output. The environment output includes the green land of parks per capita (GL), the annual mean concentration of $PM_{2.5}$ [26], [27], the volume of discharged industrial waste water (VIWWD)

TABLE 1. Input indexes for the evaluation of land utilization efficiency.

City\Index	IF	RP	IL	CL	RL	OL
Guangzhou	570358.60	14043.5	186.37	60.24	212.75	208.28
Shenzhen	407816.38	11908.4	273.42	35.73	208.61	403.69
Zhuhai	138975.45	1675.3	80.94	18.21	56.68	93.57
Foshan	351203.93	7462.7	37.18	16.03	81.93	83.71
Jiangmen	71528.91	4544	12.71	1.79	9.53	15.42
Zhaoqing	71119.63	3846	31.93	5.81	37.32	38.34
Huizhou	111261.76	4775	65.15	17.32	79.18	92.27
Dongguan	155745.80	8261.4	367.94	57.38	277.17	360.66
Zhongshan	114901.46	3230	32.78	5.54	39.26	38.99

Notes: The unit of IF and RP is million yuan and thousand, respectively. The units of IL, CL, RL and OL are all km^2.

TABLE 2. Output indexes for the evaluation of land utilization efficiency.

City\index	Environment				Economy			
	GL	$PM_{2.5}$	VIWWD	VSDE	RLS	VTI	VSI	GDP
Guangzhou	22.09	36	19326	20726	69742.6469	140907.21	2551.63	1419.33
Shenzhen	16.45	26	10891	4749	104019.078	141669.51	57251.88	1674.112
Zhuhai	19.70	30	4379	3734	24751.6557	12995.12	7258.85	1345.483
Foshan	13.91	33	14107	34273	51041.1711	31067.79	30654.66	1158.91
Jiangmen	17.78	32	9000	12204	7139.2242	47646.90	59253.22	533.741
Zhaoqing	20.39	24	6567	19932	3015.678	7603.401	919.645	511.7799
Huizhou	17.85	35	6137	17297	6345.4505	14062.96	11138.46	716.0521
Dongguan	22.99	37	17245	67608	26089.1989	29824.47	25119.48	826.8217
Zhongshan	18.41	36	7097	7500	1418.2889	14641.27	4455.723	994.7133

Notes: The unit of GL, the concentration of $PM_{2.5}$, VIWWD, and VSDE is m^2, $\mu g/m^3$, ten thousands of tons, and ton, respectively. The unit of RLS, VTI, VSI and GDP is million yuan.

and the volume of sulphur dioxide emission (VSDE). These output indexes are presented in Table 2.

The data of the above input indexes and output indexes come from China City Statistical Yearbook (2020), China Land and Resources Statistical Yearbook (2020) and Guangdong Statistical Yearbook (2020). The data for $PM_{2.5}$ comes from the government web of Department of Ecology and Environment of Guangdong Province.

The GL and $PM_{2.5}$ are in the first group of economic output indexes. RLS, VTI, VSI and GDP are the second group of environmental output indexes. Additionally, the output indexes include benefit output indexes and cost output indexes. The higher value of output indexes and the lower value of cost output indexes, then the higher efficiency of a DMU. For convenience, this paper transforms the cost output index, i.e., the annual mean concentration of $PM_{2.5}$ index, into a benefit output index. Denote the value of cost output index by $f_j (j = 1, 2, \ldots, n)$. Then, the cost output index can be transformed as follows:

$$f_j' = max_{j=1,2,\ldots,n} \{f_j\} - f_j$$

Therefore, this paper applies the transformed values of cost output indexes into the proposed models in **Section IV**.

B. THE CONVERGENCE TEST AND THE EVALUATION OF GAME CROSS EFFICIENCY WITH INDEX GROUPS

In order to eliminate the influence of different physical dimensions and measurements, this paper normalizes the data of input indexes and output indexes in the unit interval [0,1]. Then, construct the programmings according to Eqs. (2)-(6) and solve these programmings by the algorithm in [16]. Subsequently, construct the programmings according to Eqs. (8) and (9) and solve these programmings by the algorithm (IA) proposed in this paper. Finally, this paper obtains all CCR, CCG, ICCR, and ICCG values of each DMU.

TABLE 3. CCR, CCG, ICCR, ICCG values and ranks given the group order of output indexes as order 1.

City\index	without k				k = 4			
	CCR	s_1	CCG	s_2	ICCR	s_3	ICCG	s_4
Guangzhou	1.0000	1	0.8148	6	1.0000	1	0.8155	6
Shenzhen	1.0000	1	0.9855	2	1.0000	1	0.9859	2
Zhuhai	1.0000	1	1.0000	1	1.0000	1	1.0000	1
Foshan	1.0000	1	0.9098	5	1.0000	1	0.9101	5
Jiangmen	1.0000	1	1.0000	1	1.0000	1	1.0000	1
Zhaoqing	1.0000	1	0.9697	3	1.0000	1	0.9702	3
Huizhou	0.7930	3	0.6999	8	0.7930	3	0.7004	8
Dongguan	0.9735	2	0.8034	7	0.9735	2	0.8043	7
Zhongshan	1.0000	1	0.9311	4	1.0000	1	0.9320	4

City\index	k = 5				k = 6			
	ICCR	s_5	ICCG	s_6	ICCR	s_7	ICCG	s_8
Guangzhou	0.9991	2	0.8080	6	0.5617	5	0.4867	8
Shenzhen	1.0000	1	0.9588	3	0.7600	3	0.7093	6
Zhuhai	1.0000	1	1.0000	1	1.0000	1	1.0000	1
Foshan	1.0000	1	0.8921	5	1.0000	1	0.8699	4
Jiangmen	1.0000	1	1.0000	1	1.0000	1	1.0000	1
Zhaoqing	1.0000	1	0.9624	2	1.0000	1	0.9496	3
Huizhou	0.7930	3	0.6892	7	0.7930	2	0.7112	5
Dongguan	0.7397	4	0.6391	8	0.7193	4	0.5960	7
Zhongshan	1.0000	1	0.9555	4	1.0000	1	0.9961	2

(a) The convergence test for the algorithm (IA) is given as follows. The data in Table 1 and Table 2 are utilized in the convergence test. By utilizing the algorithm (IA) proposed in this paper and the algorithm in [16], the values of CCG are shown in Fig. 1 and Fig. 2, respectively. All results and the iterations for different cities are drawn with different markers. In Fig. 2, the curve of Jiangmen and the curve of Zhuhai coincide on the top. Furthermore, with the increasing of iterations, the CCGs of the DMUs j tend to a stable state. Although the initial values of the algorithm (IA) proposed in this paper and the algorithm in [16] are different, the final results are the same. According to the above analysis, it can be found that the proposed algorithm (IA) can be directly used to calculate the CCGs in [16] if the differences between different groups of output are not considered in the solving process. Comparing with the algorithm proposed in [16], the algorithm (IA) needn't take Eqs. (3) and (4) into account but the final results are still the same as that obtained by the algorithm in [16]. Therefore, in terms of the calculation of CCGs, the algorithm (IA) has a better performance than algorithm in [16].

The numerical values of CCR and CCG are listed in Table 3.

The convergence of algorithm (IA) for calculating ICCG with different number of the first group of outout indexes k is shown in Fig. 3. It can be observed that the iteration is convergent as the result of Theorem 1. The subgraph **a** in Fig. 3 represents the result with $k = 4$, i.e., the constraint $\sum_{r=1}^{4} \mu_r \leq \sum_{r=5}^{8} \mu_r$ exists in Eqs. (8) and (9).

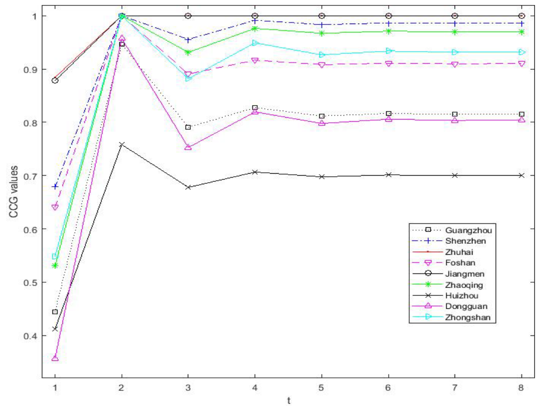

FIGURE 1. Convergent curves for CCG obtained by the algorithm in [16].

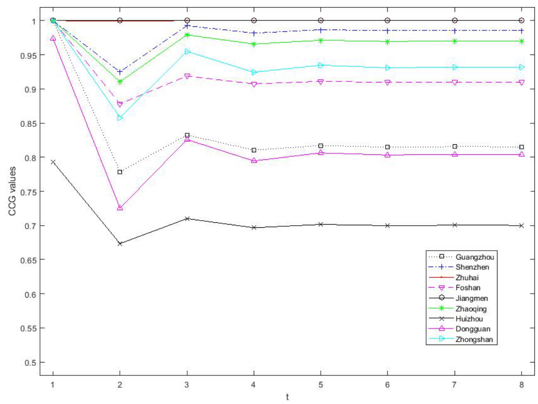

FIGURE 2. Convergent curves for CCG obtained by the algorithm (IA).

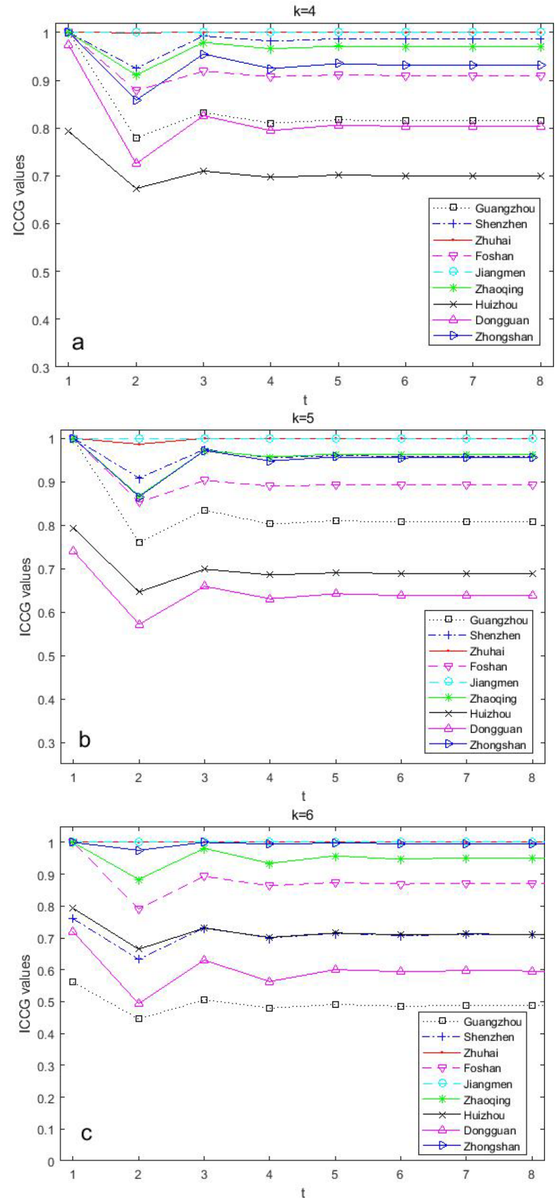

FIGURE 3. Convergent curves for ICCG with $k = 4$ (subgraph a), $k = 5$ (subgraph b), and $k = 6$ (subgraph c).

This constraint implies that the decision makers prefer the environment index group GL, $PM_{2.5}$, VIWWD, VSED than the economy index group RLS, VTI, VSI, GDP. The subgraph **c** in Fig. 3 represents the result with $k = 6$. In this case, it is assumed that the decision makers pay more attention to the index group VSI, GDP than the others.

(b) The comparison between the values of ICCR, ICCG, CCR, and CCG is given as follows. Since the output indexes are not divided into different group in the process of solving CCR and CCG, the final results are not changed in Table 3 and Table 4. Since the values of ICCR and ICCG are related to the groups of output indexes, in Table 3, these values are computated with the group order of output indexes in Table 2, that is, the order, denoted as $\mathbf{Order_1}$, is GL, $PM_{2.5}$, VIWWD, VSDE, RLS, VTI, VSI, and GDP.

These values in Table 4 are obtained with the group order (denoted as $\mathbf{Order_2}$) of output indexes given as below:

RLS, VTI, VSI, GDP, GL, $PM_{2.5}$, VIWWD, and VSDE;

In this case, it changes the order between environment indexes and economy indexes.

The number of classes of DMUs (the cities) divided by CCR is lower than that by ICCR. In Table 3, for $k = 5$ and $k = 6$, the number of classes by ICCR is 4 and 5, respectively, while the number is just 3 for CCR. For all k in Table 4, the number of classes by ICCR is at least 5, while the number is only 3 for CCR. The discernibility of CCR is lowest in CCR, ICCR, CCG and ICCG. It can be also seen from Table 3 and Table 4 that the discernibility of CCR and ICCR is lower than ICCR and ICCG, respectively, since the number of classes by CCR and ICCR is at most 6 but the number is at least 7 for CCG and ICCG.

For the land efficiency evaluation by DEA in the paper, one of our motivation is to find out that whether or not the different preference to different group of output indexes have an effect on the rank of DMUs. If the importance of the group of environment output indexes, i.e., {GL, $PM_{2.5}$, VIWWD, VSDE}, is not higher than that of economy output indexes, i.e., {RLS, VTI, VSI, and GDP}, then there is no difference

TABLE 4. CCR, CCG, ICCR, ICCG values and ranks given the group order of output indexes as order 2.

City\index	without k				k = 4			
	CCR	s_1	CCG	s_2	ICCR	s_3	ICCG	s_4
Guangzhou	1.0000	1	0.8148	**6**	0.5632	5	0.4950	8
Shenzhen	1.0000	1	0.9855	**2**	0.7806	3	0.7339	5
Zhuhai	1.0000	1	1.0000	**1**	1.0000	1	1.0000	1
Foshan	1.0000	1	0.9098	**5**	1.0000	1	0.8696	4
Jiangmen	1.0000	1	1.0000	**1**	1.0000	1	1.0000	1
Zhaoqing	1.0000	1	0.9697	**3**	1.0000	1	0.9861	3
Huizhou	0.7930	3	0.6999	**8**	0.7930	2	0.7065	6
Dongguan	0.9735	2	0.8034	**7**	0.7751	4	0.5943	7
Zhongshan	1.0000	1	0.9311	**4**	1.0000	1	0.9962	2
City\index	k = 5				k = 6			
	ICCR	s_5	ICCG	s_6	ICCR	s_7	ICCG	s_8
Guangzhou	0.4429	6	0.4014	**7**	0.3598	5	0.3200	6
Shenzhen	0.5644	5	0.5121	**5**	0.5644	4	0.5181	5
Zhuhai	1.0000	1	1.0000	**1**	1.0000	1	1.0000	1
Foshan	0.7102	3	0.6095	**4**	0.6577	3	0.5495	4
Jiangmen	1.0000	1	1.0000	**1**	1.0000	1	1.0000	1
Zhaoqing	1.0000	1	1.0000	**1**	1.0000	1	1.0000	1
Huizhou	0.7807	2	0.7148	**3**	0.7807	2	0.7124	3
Dongguan	0.6463	4	0.5044	**6**	0.3023	6	0.2262	7
Zhongshan	1.0000	1	0.9912	**2**	1.0000	1	0.9959	2

Notes: the sign "s" is the corresponding rank by the value of previous column.

between the rank (s_2) of DMUs by CCG and that (s_4) by ICCG, which is in accord with the case with $k = 4$. However, if the group of environment output indexes, i.e., {GL, $PM_{2.5}$, VIWWD, VSDE}, is more important than the group of economy output indexes, {RLS, VTI, VSI, and GDP}, then according to Table 4 with $k = 4$, the rank (the column s_2) of Guangzhou and Shenzhen is decreased from 6 and 2 to 7 and 5 (the column s_6) respectively, the rank of Zhuhai and Jiangmen maintains being unchanged, and the rank of the others are all increased, which is very different from Table 3.

This changing does not mean that the rank of any cities with high GDP will definitely decrease if the environment indexes are taken great importance since Guangzhou, Shenzhen and Zhuhai are the top three with the values of GDP in these 9 cities, while Zhuhai maintains the first. This result shows that in land efficiency evaluation, if pay more attention on the environment indexes than the economy indexes, the ranking of DMUs obtained by ICCG can be changed from CCG according to the Eqs. (8)-(10) in this paper. Taking the values of ICCG for $k = 4$ in Table 3 and Table 4, the cities Zhuhai and Jiangmen are revealed as the best two city for both the economy and the environment.

According to Table 4, different preferences on different groups of output indexes make the final ranking of DMUs change. The divergence between rankings of some cities, such as Shenzhen and Zhuhai, measured by ICCG may be huger than that calculated by CCG. The huger divergence further demonstrates that the rank of Shenzhen in CCG attaches more importance to GDP than the environment.

However, ranking DMUs by ICCG may be more difficult than by CCG since the number of same ranking of cities obtained by ICCG is more than CCG.

(c) Parameters adjustment analysis is provided as follows. As shown in Table 3 and Table 4, the index dependency of DMUs can be analyzed by adjusting the parameter k in Eqs. (8) and (9). Through change the value of parameter k, decision makers' preference on output indexes are changed. For example, change the value of parameter k from 4 to 5 in Table 3, then the index group GL, $PM_{2.5}$, VIWWD, VSDE is changed as GL, $PM_{2.5}$, VIWWD, VSDE, RLS. When the *RLS* index is not very important, the ICCG ranks of the game cross efficiencies of Shenzhen and Dongguan are decreased. This means that these two DMUs are more dependent on the index RLS, i.e., the revenue of the sale of land than others output indexes. When k changes from 5 to 6, the group GL, $PM_{2.5}$, VIWWD, VSDE, RLS is changed as GL, $PM_{2.5}$, VIWWD, VSDE, RLS, VTI. In this situation, the ranks of Guangzhou, Shenzhen and Zhaoqing decline, and the index VTI contributes more on these three cities in this year. It can be found from Table 3 and Table 4 that: despite the change of value of parameter k, the ranks of Zhuhai and Jiangmen always fall into the first class. These two cities are the best ones with the highest land utilization efficiency. To some extent, the others has the potential to enhance the land utilization efficiency.

By the above analysis, the values of the current ICCG are obtained from the improved game cross efficiency DEA model in Eqs. (8)-(10) and this paper provides a convergent algorithm to solve the model. ICCG can evaluate the performance of DMUs in a new view which is different from CCG. Furthermore, it can be used to judge the dependency on some output indexes for DMUs.

VI. CONCLUSION AND DISCUSSION

For the efficiency evaluation in the situation that there exists a competition between DMUs, CCG values proposed in [16] provides a reference. In order to handle the problem that DMU has different preferences on different groups of output indexes. A new game cross efficiency DEA model with index groups and adjustable parameters is proposed. Then, this paper develops a convergent algorithm to solve the new model and calculate the values of ICCG. ICCG values give a new reference for efficiency evaluation of DMUs from a different view. It should be pointed that the proposed algorithm can also compute CCG values without dividing the output indexes into different groups.

In detail, if the differences of output indexes are not considered, the CCG values obtained by the proposed method are same with that obtained by the algorithm in [16].

Comparing with the typical CCR values, the divergences between DMUs measured by CCG and ICCG values are huger. Furthermore, the differences between groups of output indexes are considered in the solving process of ICCG values, while the differences are neglected in CCG values. Thus, the results of efficiency evaluations of land DMUs measured by CCG values and ICCG values are different. According to the analyses in Section IV (B), the group of environment indexes are preferred than that of economy indexes in the

ICCG values, which result in the fact that the ranking of some cities decrease even the GDPs of these cities are high.

Since parameter k in the models (8) and (9) determines the number of output indexes in different groups, the efficiency evaluation of a DMU changes with the change of the parameter k. Take values of the parameter k as 4, 5, 6, respectively. Then, it can be found that Zhuhai and Jiangmen always rank the first by ICCG. Apparently, this stable result cannot be obtained by CCG in [16].

In summary, this paper shows that it needs to consider the mutual evaluation and competition between DMUs for the land utilization efficiency in a region. By focusing on the PRD cities in China, this paper chooses the input indexes and output indexes closely related to the land utilization, and divides the output indexes into two groups: environmental indexes and economy indexes. Using the real data, this paper tests the convergence of the algorithm for the model by the comparing of the proposed algorithm and the algorithm in references. The result shows that ICCG of the proposed model can reveal more information than CCG, such as: no matter what kinds of output index groups decision makers prefer, environment indexes or economy indexes, there exists two cities, Zhuhai and Jiangmen, which have the best performance. However, there are two cities, Guangzhou and Shenzhen, which have a good performance only if decision makers prefer economy indexes — this cannot be obtained from CCG. There are different dependencies on output indexes for different cities, in fact, the efficiency of two cities, Shenzhen and Dongguan, is dependent highly on the revenue of the sale of land.

It is known that the DEA models are widely used to many other fields, such as supply chains, shortest path problems, transportation problems, public school assessments, and voting systems. The performance that the ICCG model proposed in this paper applied to these problems needs to be further validated. This is also our research interest in the future.

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